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ABSTRACT

Personal and environmental variables that characterize students who are involved in different types of interactions in different types of classroom settings were studied. Organizational, behavioral, task, response, and initiation interactions were studied in four eighth-year science classrooms using both student-centered and teacher-directed curricula. Three teachers and 108 students in a large metropolitan secondary school in Brisbane (Australia) participated in the study. The study was conceptualized within the Lewinian B=f(P,E) framework (K. Lewin; 1936, 1951), and involves multivariate analysis of selected "P" variables: student personality, motivational, and cognitive characteristics, and "E" variables: curriculum materials and characteristics of the learning environment. Attempts to interpret the significant regression coefficients by referring to the original raw data indicate that the significance is an artifact of the regression model trying to accommodate extreme scores. Whenever data from complex environments are to be analyzed, the techniques applied must not attempt to fit the data into an artificial model. Alternative modeling procedure may be more appropriate. Thirteen tables and 8 figures present study data, and there is a list of 24 references. (SLD)

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CHARACTERISTICS OF INTERACTORS IN DIFFERENT TYPES OF CURRICULA SETTINGS: A LEARNING EXPERIENCE IN THE USE AND MISUSE OF REGRESSION ANALYSIS

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ABSTRACT

This study attempts to identify personal and environmental variables which characterize students who are involved in different types of interactions in different types of classroom settings. Organizational, Behavioural, Task, Response and Initiation interactions are studied in Year 8 science classrooms using both student-centred and teacher-directed curricula. The presumably appropriate multiple regression model is used within a Lewinian B=f(P,E) framework to identify the "P" and "E" variables which determine student involvement in the different types of interactions "B". Attempts to interpret the significant regression coefficients by referring back to the original raw data indicate that the significance is an artifact of the regression model trying to accommodate a handful of extreme scores. Alternative and more appropriate modelling procedures give a more accurate indication of what is really happening.

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Barry C. Dart John A. Clarke and David Chant.

INTRODUCTION

A number of recent reviews and research studies focussing on differential participation of boys and girls in classroom interaction have highlighted the inadequacy of the sex of the student as a determinant of involvement in classroom interaction (Clarke and Dart, 1987; Dart and Clarke, 1988; Hacker, 1986). Subsequently, it was suggested that a more appropriate procedure for future research would be to use the criterion of whether students participate or not rather than whether they are boys or girls in order to identify significant personality or environmental characteristics which influence participation (Dart and Clarke, 1988). This paper attempts to identify those factors which determine involvement in different types of interactions in structurally different classroom settings.

The study focusses on four Year 8 science classrooms studying two different types of curriculum units. The latter units are a student-centred, activity-based unit "***Mice and Men***" (ASEP 108; 1973) and a chapter of a textbook "***Solutions***" (Stannard and Williamson; 1979) taught in a more traditional teacher-centred way. The study is conceptualized within the Lewinian B = f(P,E) framework (Lewin; 1936, 1951) and involves a multivariate analysis of selected "P" variables: student personality, motivational and cognitive characteristics, and "E" variables: curriculum materials, and characteristics of the learning environment.

The particular variables used in the study are based on an empirical and theoretical analysis detailed elsewhere (Clarke, 1987). The specific "P" variables used are Conceptual Level (personality), Locus of Control (motivation) and Piagetian Level and General Scholastic Aptitude (cognition). The specific "E" variables are the two curriculum units and student perceptions of the psychosocial characteristics of their science classrooms. The particular "B" variables focussed on here as the dependent variables are different types of classroom interaction.

TYPES OF INTERACTIONS

The classification used here has been used previously by the authors (Clarke and Dart, 1987; Dart and Clarke, 1988). It is based on the major verbal activities that occur in classrooms and the interactions are categorised according to source and type of interaction.

(a) Sources of interaction: Teacher-to-Student (T->S)

Student-to-Teacher (S->T)

(b) Types of interaction

T->S interactions are classified into three types:

Organisational -

> T: Now the monitors who gave out the mice come out; the monitors who give out the mice containers give those out please. And somebody from each bench come and get the scales.

Behavioural -

> T: I'm not interested in whose fault it was but I'll see you also. That will be three. I'm getting tired of other people saying it was their fault. People either have to learn how to behave or suffer the consequences.

Task -

> T: What do we mean when we say something is biodegradable?

S->T are classified into two types:

Response -

> Andrew: It can be broken down by bacteria and fungi.

Initiation -

> Peter: Is that particles of a solute dissolved in a solvent?

THE STUDY

Sample

The sample consists of four Year 8 science classes in a large metropolitan secondary school in Brisbane, Australia. The classes contain 108 students taught by 3 teachers. Some of the characteristics of the sample are summarized in Tables 1 and 2.

Tables 1 and 2 somewhere here

Data Collection

The dependent variable, classroom dialogue, was collected on audiotape. All independent variable data were collected by questionnaire. Six science lessons, three in "Solutions" and three in "Mice and Men", each lasting for 40 minutes, were audiotaped for each class. All lessons occurred in a science laboratory and a tape recorder was placed on each of the six laboratory desks and on the front demonstration desk. Students were allocated to permanent laboratory seating positions by school policy and identified themselves on tape at the beginning of each lesson. These procedures along with the normal use of names in interaction, ensured that all students could be identified. Each tape was later transcribed and used to produce a complete transcription of each lesson. These transcriptions are used in this study.

A brief description of the independent variables and how they were measured is given below.

Variable	Description	Measuring Instrument
"P" Variables:		
Conceptual Level (CL)	Individual differences in social cognition within a framework of developmental maturity	"Interpersonal Topical Inventory" (ITI) (Tuckman; 1964)
Locus of Control (LOC)	Perception of the influence of self and others on own behaviour	"Intellectual Achievement Responsibility Questionnaire" (IAR) (Crandall, Katkovsky and Crandall; 1965)
Piagetian Level (PIAGLEV)	Ability to process information in the absence of concrete props	"Bond Logical Operations Test" (BLOT) (Bond; 1976)
General Scholastic Aptitude (SCHLAPT)	Ability to cope with educational environments	"Test of Learning Ability" (TOLA) (ACER; 1974)
"E" Variables:		
Curriculum	Two different types of curricula	"Mice and Men" (ASEP 108; 1973) "Solutions" (Stannard and Williamson; 1979)
Learning Environment	Perceptions of the psychosocial characteristics of the learning environment	"Individualized Classroom Environment Questionnaire" (ICEQ) (Rentoul and Fraser; 1979)

The ITI classifies individuals into 1 of 4 levels on a continuum of maturity of social interaction. The IAR identifies "internals" or people who feel a sense of responsibility for their academic successes and failures and "externals" who feel that their achievements are at the whim of external forces. The BLOT categorizes individuals as being in the concrete, abstract or concrete-abstract transition stage of cognitive development while TOLA is a general measure of scholastic aptitude. The ICEQ has subscales of Personalization (PERSON), Participation (PARTIC), Independence (INDEP), Investigation (INVEST) and Differentiation (DIFFER) which are defined in detail elsewhere (Rentoul & Fraser; 1979). Student age and sex were also included as "P" variables.

The "B" or dependent variables, the interactions, have been classified earlier as Organization (ORGAN), Behavioural (BEHAV), Task (TASK), Response (RESP) and Initiation (INIT). Since these occur in the two different curricula areas, "Mice and Men" (M) and "Solutions" (S), there are 10 different dependent variables, MORGAN, MBEHAV, MTASK, MRESP, MINIT, SORGAN, SBEHAV, STASK, SRESP and SINIT.

INITIAL ANALYSIS

Because this study is an exploratory one, multiple regression analysis is a useful and appropriate technique (McArthur and West, 1974; Walberg, 1971). Further, there are good statistical reasons for using multiple regression analysis. These are summarized as they apply in person-environment interaction studies by Fraser and Rentoul (1980) who in turn are drawing on Kerlinger and Pedhazur (1973), Kaufman and Sweet (1974) and Cohen and Cohen (1975).

1. The multiple regression technique offers a variety of solutions in the case where predictors are intercorrelated.

2. It strengthens statistical power by using continuous variables rather than reducing the data to a number of levels.

3. The technique yields useful estimates of the amount of variance explained in each criterion by the predictor variables.

4. It allows the inclusion of interaction terms.

5. It can be used to test the combined effects of sets of variables.

From the transcripts, the five types of interactions defined above were identified and allocated to the appropriate student in each of the two curriculum areas. The ten regression analyses were carried out by applying the SAS REG and RSREG procedures (SAS/STAT; 1987:773-895) to the following general model

TYPE OF INTERACTION (MORGAN,.....SINIT) with AGE, SEX, CL, LOC, PIAGLEV, SCHLAPT, PERSON, PARTIC, INDEP, INVEST, DIFFER, plus all second order factors.

The REG procedure carries out diagnostic and collinearity tests on the data. It detected unacceptable instability in the results associated with the variable AGE. This variable was deleted from subsequent analysis.

The outcomes of the regression analyses are summarized in Table 3.

Table 3 somewhere here

The normal procedure used to identify important main effects in regression is to be guided by the sign and significance level of the regression coefficients. Interaction terms are more complex and not as easily interpreted. They have been explored by researchers plotting regression surfaces (e.g. Fraser and Fisher, 1983; Marjoribanks, 1980). In our case, attempts to interpret the regression surfaces led us to question whether the regression process is applicable to our data. Two situations deemed significant by the regression procedure are discussed here by way of example.

SUBSEQUENT ANALYSIS: A COMPARISON OF MULTIPLE AND LOGISTIC REGRESSION.

For ease, the discussion is mainly restricted to relationships between sets of three variables, of the form of two predictors and one criterion.

Example 1. Predictors: PIAGLEV and INDEP;
Criterion: MBEHAV

Table 4 gives a slight aggregation of the three-way frequencies for these variables. The raw (or completely disaggregated) data would typically be used as input to a regression analysis with MBEHAV as the criterion. Table 4 reveals three major points:-

(i) There are relatively few non-zero interactions (20 out of 108).

(ii) The larger interactions (MBEHAV = 2 and 3) occur at low PIAGLEV levels and, on 4 out of 5 occasions, at high INDEP levels (see also Table 5).

(iii) Any causality imputed to (ii) cannot be reversed. Low PIAGLEV levels and high INDEP levels occur frequently in conjunction with zero interactions.

Table 4 about here

Table 5 aggregates Table 4 into dichotomies for PIAGLEV and INDEP. 'High' and 'Low' refer to being greater or less than the mean response indicated on Table 4.

Table 5 about here

The first plot in Figure 1 gives the scatter-plot of the data, reinforcing the above impressions. The second plot fits a data-weighted surface to the data, highlighting the relationships present without prejudicing them by formal model fitting.

Figure 1 about here

Raw Data	DWLS
Linear	Quadratic

Formal model-fitting (the lower two plots in Figure 1) reveals the deficiencies of multiple regression. The linear fit underestimates the region with high interactions, but in attempting to accommodate this region, overestimates much of the region of zero interactions. The quadratic fit, allowing for curvature and tilt, appears to be a substantial improvement over the linear fit, at the expense of a more complex interpretation.

Table 6 about here

Table 7 about here

However the results of multiple regression analyses given in Tables 6 and 7 show that neither model fits the data at all well. Using conventional regression diagnostics to identify outliers and remove them removes nearly all the high interactions (i.e. the larger values of MBEHAV), leaving a dichotomous criterion. The point of the diagnostic exercise is to demonstrate the inadequacy of multiple regression modelling, not to suggest that such a dubious process should be used to analyse the data. The data also contain inliers or points of undue influence; these are outlying combinations of the predictor variables which least squares estimates are well known to load heavily on. Although not detailed here, they tend to be associated with the non-zero interactions not already identified as outliers.

A formal deduction from the second linear fit (stage 2 in Table 7) is that the greater the value of PIAGLEV, the less the number of interactions and conversely, the less the value of PIAGLEV, the greater the number of interactions, and this state of affairs does not vary significantly with the value of INDEP.

Both contentions distort the facts. Larger values of PIAGLEV are overwhelmingly associated with zero interactions. There is no smooth passage to this state of affairs. As the second plot in Figure 1 suggests, there is a region of zero interactions, suddenly converted to a region where interactions do occur and this region consists mainly of low values of PIAGLEV. However, low values of PIAGLEV are still far more frequently associated with zero interactions than non-zero interactions. In probabilistic terms, if we condition on low values of PIAGLEV (so PIAGLEV still plays the role of a predictor) there is a probability distribution over MBEHAV whose major atom is at zero. The probability of at least one interaction is still absolutely small, even though relatively much greater than the corresponding probability for larger PIAGLEV. This is a very different interpretation than that offered by multiple regression with its causal overtones of low values of PIAGLEV causing high values of MBEHAV. There is a converse statement to the effect that if we condition on 2 or 3 interactions, then the value of PIAGLEV will be low; this casts MBEHAV as the predictor and PIAGLEV as the criterion, contrary to the usual flow.

It is preferable to treat the three variables as an ensemble and ask how their frequencies co-vary. This leads naturally to a log-linear analysis (which avoids causal links of predictor to criterion) or a logistic regression which preserves the roles of criterion and predictor. To preserve the comparison with multiple regression, we pursue a logistic regression approach. Basing the analysis on the aggregation in Table 5 leads to significant effects of both predictors and their statistical interaction ($P<0.001$ in each case, the analysis is carried out by the CATMOD procedure in SAS(1987)). Four fitted probability distributions are derived, one for each combination of levels of PIAGLEV and INDEP. These are given in the first part of Table 8. It is apparent that the dominant predictor is PIAGLEV, smaller values of PIAGLEV lead to the possibility of greater

interactions in combination with larger values of INDEP the probability of at least 2 interactions climbs to 0.14, the mass of the distribution still falling at zero interactions. We do better using the raw data essentially displayed in Table 4. Three combinations of PIAGLEV and INDEP are displayed in the second part of Table 8 (they are close to mean values for MBEHAV=0,2,3.

Table 8 about here

At the low PIAGLEV, high INDEP combination (itself a rare event), there is now a 75% chance of at least 2 interactions, but this probability reduces rapidly to much less than half as PIAGLEV and INDEP approach their mean values. The methodology is not restricted to a two or three variable at a time approach, a formal analogy with multiple regression uses the same set of predictors as in the previous section and finds them all significant, in that they are associated with variability in the incidence rates of at least one of the atoms 0,1,2,3 observed for MBEHAV. These results are not presented here, but the low frequency of non-zero responses creates instability problems with so many predictors present in the model; one attempt at parsimony is that given here.

Example 2. Predictors: PIAGLEV and PARTIC;
Criterion: SBEHAV

Table 9 gives a slight aggregation of the three-way frequencies for these variables.

Table 9 about here

There are 39 non-zero interactions and a greater range of values for SBEHAV, hopefully making multiple regression more applicable than in Example 1. The surfaces in Figure 2 suggest that the response surface might reasonably be fitted by a quadratic with a minimum and that a plane will fail to capture this behaviour.

Figure 2 about here

Raw Data	DWLS
Linear	Quadratic

Note that for large values of SBEHAV (say, 4 or more) the values of PIAGLEV are not particularly extreme and only at the greatest values of SBEHAV are the associated values of PARTIC extreme. Table 10 aggregates SBEHAV into dichotomies for PIAGLEV and PARTIC and Table 11 gives the fitted probability distributions over values of SBEHAV.

Table 10 about here

Table 11 about here

The two predictors and their statistical interaction are significant, but, as in Example 1, the passage to the region where large interactions occur (say, SBEHAV at least 4) is not smooth, as the imposed multiple regression fits given in Tables 12 and 13 suggest. Most importantly, it is again only the possibility of large numbers of interactions that is attained at small values of PIAGLEV and PARTIC, the dominant atom of the distribution of SBEHAV is still at zero and is in excess of one half except for the very extreme choice taken in the last row of Table 11.

Table 12 about here

Table 13 about here

CONCLUSION

From the results of the initial analysis, it would seem intuitively that some form of intervention in relation to the "P" and "E" variables would be useful so as to increase (Task) and decrease (Organizational and Behavioural) interaction. For example, the multiple regression analysis for MBEHAV produces significant regression coefficients for SCHLAPT, PIAGLEV and INDEP. Little can be done to influence the scholastic aptitude of the individual measured by TOLA. However, if PIAGLEV is an important variable in interaction as the results of the analysis suggest, and if the aim is to improve appropriate classroom interaction, then programs which attempt to improve formal reasoning would be appropriate.

Attempts to improve the performance of concrete thinkers and to promote cognitive growth through various instructional procedures are numerous and reviewed extensively elsewhere (e.g. Clarke, 1987; Lawson, Costenson and Cisneros, 1986). The outcomes are somewhat equivocal. A possible explanation for the equivocal results in this area might be the use of inappropriate correlation and regression models that produce Piagetian level as a statistically significant explainer of the criterion variable.

Similar reservations could be held about modifying INDEP, on the basis of correlational and regression models. It should be noted that Fraser (1981) reports a successful modification of student perceptions. However the identification of the appropriate variable to be modified was not based on a regression model.

The message here is that whenever data from complex natural environments is to be analysed, it is necessary to ensure that the analytical techniques applied are appropriate to this natural complexity and do not attempt to fit the data into an artificial model. An alternative approach that avoids the pitfalls of regression is the use of log-linear models to look at the relationship between variables and, when some causality is imposed, the closely allied method of logistic regression. Problems arise in these methods due to the sparseness of the criterion variables (larger numbers of interactions occur with relatively low frequency), but can be overcome with careful aggregation of the data. A major defect of the multiple regression approach is its inability to adequately model the larger number of interactions, hence the investment in alternative models is well worth while.

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Table 1
General Characteristics of Teachers in the Study

Teacher	Age (yrs)	Sex	Teaching experience (yrs)
A	45	Male	24
B	30	Male	8
C	33	Female	13

Table 2
Distribution of Teachers and Students in Classes

Class	Teacher	N of Students		
		Male	Female	Total
1	A	13	12	25
2	B	15	13	28
3	C	14	14	28
4	C	15	12	27

TABLE 3: Summary of the Outcomes of Multiple Regression Analyses of Different Types of Interactions in Two Curriculum Areas

---

(a) MICE AND MEN

(i) Organizational (MORGAN)
Insufficient interactions for analysis

(ii) Behavioural (MBEHAV)
SCHLAPT
PIAGLEV
INDEP
PERSON*SCHLAPT
PARTIC*SCHLAPT

(iii) Task (MTASK)
No significant variables

(iv) Response (MRESP)
No significant variables

(v) Initiation (MINIT)
No significant variables

(b) SOLUTIONS

(i) Organizational (SORGAN)
SCHLAPT
PIAGLEV
PERSON*SEX
INDEP*PERSON

(ii) Behavioural (SBEHAV)
PERSON*ITI
PERSON*PERSON
PARTIC*PERSON
PARTIC*PARTIC
INDEP*SCHLAPT
INVEST*INVEST
DIFFER*INDEP

(iii) Task (STASK)
PERSON
INDEP*SEX
DIFFER*INVEST

(iv) Response (SRESP)
No significant variables

(v) Initiation
No significant variables

Table 4.
Three-way frequencies for MBEHAV x PIAGLEV x INDEP

PIAGLEV	MBEHAV 0 INDEP 12	13-16	17	18	19-20	21	22	23	24	25-26	27	28	29	30	31	32-35	MBEHAV 1 INDEP 11	12	17	18	21	22	23	24	27	29	31	36	42	MBEHAV 2 INDEP 21	28	31	MBEHAV 3 INDEP 29	31
7																																1		1
8										1																1		1					1	
9																													1					
10																																		
11					1				1		1																							
12								1																										
13		1					1	1				1	1																					
14			1	1							1	1						1									1			1				
15									1																									
16		1																																
17		2					1		1							1																		
18				1								1			1																			
19										2										1														
20	1	1		1	1	1	1	1	1										1								1						
21		1							1	1				1	1																			
22					3		1					1	1																					
23		1	1			1					1			1		1																		
24		3			3	1					1	1			1	1			1		1			1										
25					1		1	1						2		1				1														
26			1							1									1															
27							1					1																						
28		1																			1		1											
29		4	1	1	3	1				1	2				1	1																		

Grand mean (PIAGLEV): 21.1
SD:6.4

Grand mean (INDEP) : 22.6 SD : 5.9

Table 5
Three-way frequencies dichotomized by mean responses

	MBEHAV							
	0		1		2		3	
	INDEP		INDEP		INDEP		INDEP	
	Low	High	Low	High	Low	High	Low	High
PIAGLEV Low	19	20	3	5	1	2	0	2
PIAGLEV High	29	20	5	2	0	0	0	0
Test for Association	P_{exact}=.33		P_{exact}=.32		No test		No test	

Table 6
Regression Diagnostics (Outliers) for MBEHAV

			Stage 1		Stage 2	
	Number of Interactions	Original Frequency	Number of outliers	Updated Frequency	Number of outliers	Updated Frequency
LINEAR	0	88		88		88
	1	15		15		15
	2	3		3	2	1
	3	2	2			(an inlier)
		108		106		104
QUAD	0	88		88		88
	1	15		15		15
	2	3	1	2	1	1
	3	2	2			
		108		105		104

Table 7
Regression results for MBEHAV

	Source	Coefficient	Std Error	P-value (2 Tail)	
(~~Stage 1~~)					
L I N	PIAGLEV (P)	-0.032	0.009	<0.001	
	INDEP (I)	0.014	0.009	0.125	
	(N=108, overall P<0.001)				
Q U A D	P	-0.072	0.071	0.315	
	I	0.065	0.069	0.348	
	P^2	0.003	0.001	0.025	<-
	PxI	-0.003	0.001	0.047	<-
	I^2	0.000	0.001	0.913	
	(N=108, overall P<0.001, P_{quad}<0.001)				
(Stage [illegible])					
L I N	PIAGLEV (P)	-0.019	0.007	0.011	
	INDEP (I)	0.008	0.008	0.295	
	(N=106, overall P=0.012)				
Q U A D	P	-0.034	0.057	0.551	
	I	-0.008	0.055	0.888	
	P^2	0.001	0.001	0.187	
	PxI	-0.002	0.001	0.211	
	I^2	0.001	0.001	0.310	
	(N=105, overall P=0.008)				
(significant regression, not attributed to any one source)					

Table 8.
Fitted probabilities using logistic regression

a) Derived from Table 5.		MBEHAV				
PIAGLEV	INDEP	0	1	2	≥3	Total
high	high	0.909	0.091	0.000	0.000	1.000
high	low	0.853	0.147	0.000	0.000	1.000
low	low	0.826	0.130	0.043	0.000	0.999
low	high	0.690	0.172	0.069	0.069	1.000

b) Derived from the raw data.		MBEHAV				
PIAGLEV	INDEP	0	1	2	≥3	Total
21	23	0.870	0.129	0.001	0.000	1.000
12	26	0.690	0.225	0.081	0.005	1.001
8	30	0.115	0.144	0.187	0.554	1.000

Table 9

Three-way frequencies for SBEHAV x PIAGLEV x PARTIC

PIAGLEV	SBEHAV 0 PARTIC 20-21	22	23	24	25	26	27	28	29	30	31-34	35	36	37	38	39-40	41	42	SBEHAV 1 PARTIC 20-21	22	23	24	25	26	27	28	29	30	31-34	35	36	38	39-40	42	SBEHAV 2 PARTIC 22	26	28	35	38	41	SBEHAV 3 PARTIC 23	35	36	37	38	SBEHAV 4 PARTIC 25	28	30	36	38	SBEHAV 5 PARTIC 30	36	SBEHAV 10 PA-RT-IC 19	SBEHAV 12 PA-RT-IC 18
7																																										1					1							
8																			1																																				
9											1																																							1						
10																				1																																		
11							1				1																																												
12																																	1																					
13				1							2				1																						1																	
14												1				1																	1																					
15	1						1																													1																	
16		1									1																																											
17															1																	1								1												
18											2																																									
19											1					1																																					
20							1				3			1							1										1				1			1	1												
-22				2	1	1	5	1				1																																								
23							3										1	1	1																																	
24							2	1	1						2		2		1											1	1			1																		
25				1			2	1																				1	1																					
-27							2	2			1																																								
28							1								1																																				
29					1		2											1																																	
30						1																																													
31					1		1	1																																										
32							1								1																																				
35												1																																							

Grand mean (PARTIC):32.9 SD:5.2

Grand Mean (PIAGLEV): 21.1

Table 10
Three-way frequencies dichotomized by mean responses

	SBEHAV															
	0		1		2		3		4		5		10		12	
PARTIC	L	H	L	H	L	H	L	H	L	H	L	H	L	H	L	H
PIAGLEV Low	16	12	3	5	3	3	0	2	3	2	1	0	1	0	1	0
PIAGLEV High	13	28	5	3	1	1	1	2	0	1	0	1	0	0	0	0

Table 11.
Fitted probabilities using logistic regression

a) Derived from Table 10.

PIAGLEV	PARTIC	SBEHAV 0	1	2	3	4	5	10	≥12	Total
H	H	0.778	0.083	0.028	0.056	0.028	0.028	0	0	1.001
H	L	0.650	0.250	0.050	0.050	0	0	0	0	1.000
L	H	0.500	0.208	0.125	0.083	0.083	0	0	0	0.999
L	L	0.571	0.107	0.107	0	0.107	0.036	0.036	0.036	1.000

b) Derived from raw data

PIAGLEV	PARTIC	SBEHAV 0	1	2	3	4	5	10	≥12	Total
21	33	0.703	0.153	0.066	0.033	0.033	0.012	0	0	1.000
15	30	0.599	0.142	0.125	0.003	0.102	0.028	0	0	0.999
15	25	0.571	0.098	0.203	0	0.099	0.028	0	0	0.999
15	18	0	0	0	0	0	0	0.998	0.002	1.000

Table 12
Regression Diagnostics (Outliers) for SBEHAV

			Stage 1		Stage 2	
	Number of Interactions	Original Frequency	Number of outliers	Updated Frequency	Number of outliers	Updated Frequency
L	0	69		69		
I	1	16		16		
N	2	8		8		
E	3	5		5	No change	
A	4	6		6		
R	5	2		2		
	10	1	1			
	12	1	1			
		108		106		
Q	0	69	1	68		68
U	1	16		16		16
A	2	8		8		8
D	3	5		5		5
R	4	6		6		4
A	5	2		2	1	
T	10	1	1		1	
I	12	1	1			
C						
		108		105		103

Table 13
Regression results for SBEHAV

(Stage 1)

	Source	Coefficient	Std Error	P-value (2 Tail)	
L					
I	PIAGLEV (Pi)	-0.069	0.027	<0.012	
N	PARTIC (Pa)	-0.103	0.033	0.002	
	(N=108, overall P<0.001)				
Q	Pi	-0.485	0.193	0.013	
U	Pa	-1.314	0.237	<0.001	
A	Pi^2	0.005	0.005	0.314	
D	PixPa	-0.485	0.193	0.013	<-
	Pa^2	0.018	0.004	<0.001	<-
	(N=108, overall P<0.001, P_{quad}<0.001)				

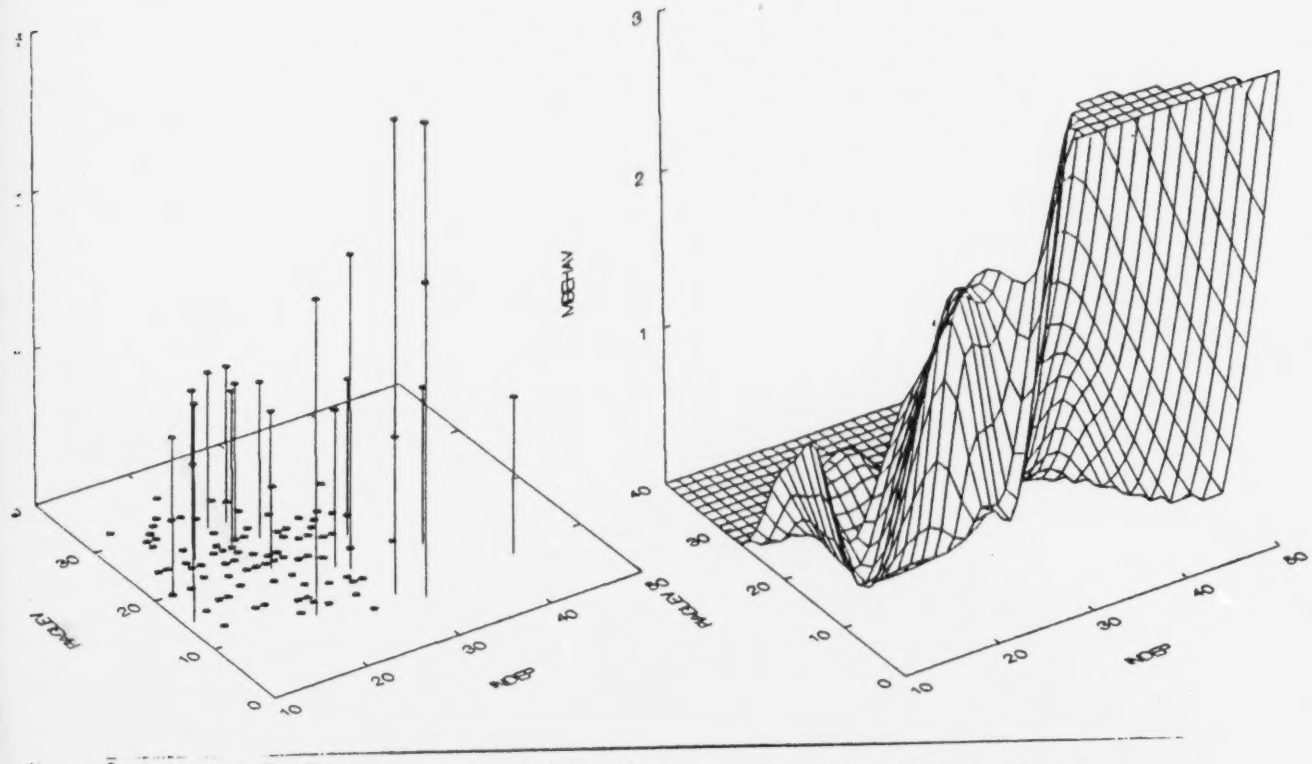
(Stage 2)

	Source	Coefficient	Std Error	P-value (2 Tail)
L				
I	PIAGLEV (Pi)	-0.052	0.026	0.009
N	PARTIC (Pa)	0.012	0.020	0.639
	(N=106, overall P=0.012)			
Q	Pi	-0.263	0.160	0.104
U	Pa	-0.373	0.249	0.138
A	Pi^2	0.006	0.003	0.012
D	PixPa	-0.002	0.004	0.698
	Pa^2	0.006	0.004	0.112
	(N=105, overall P=0.005)			

Figure 1.

Mice & Men: Raw Data

Mice & Men: DWLS Surface



Mice & Men: LS Plane

Mice & Men: Quadratic LS Surface

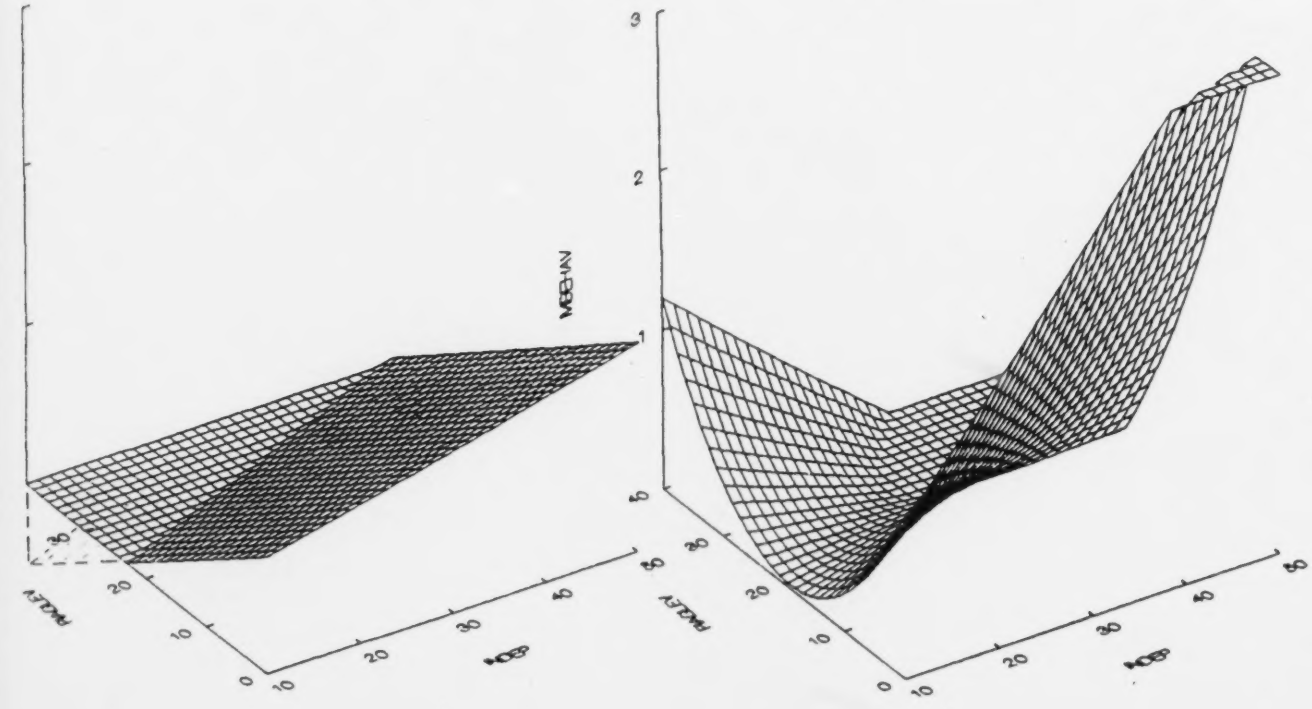
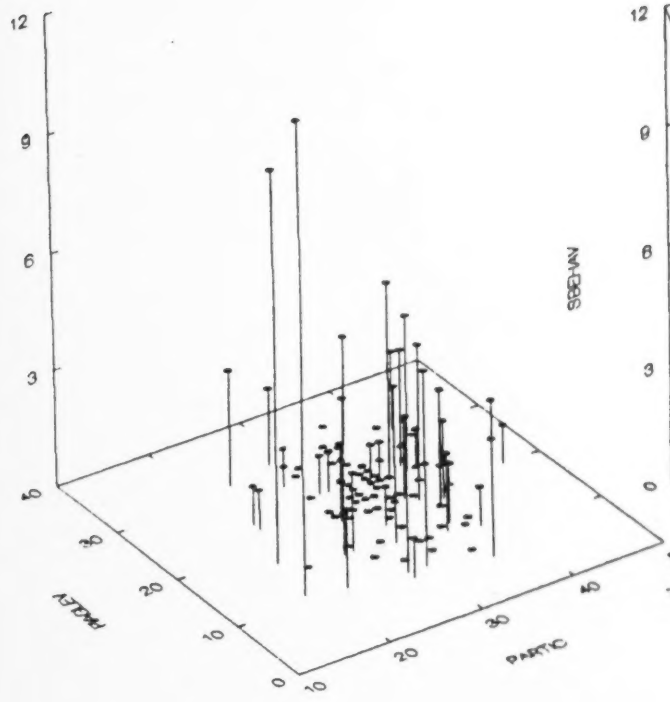
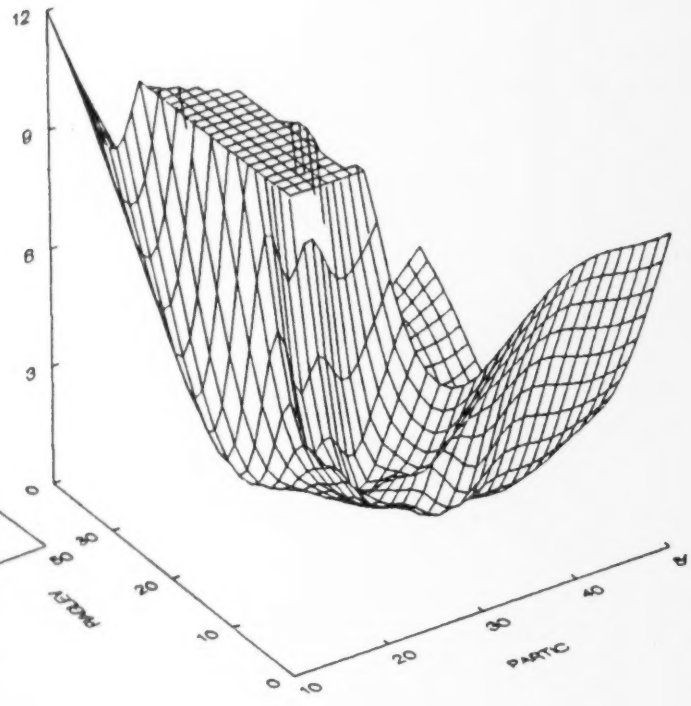


Figure 2.

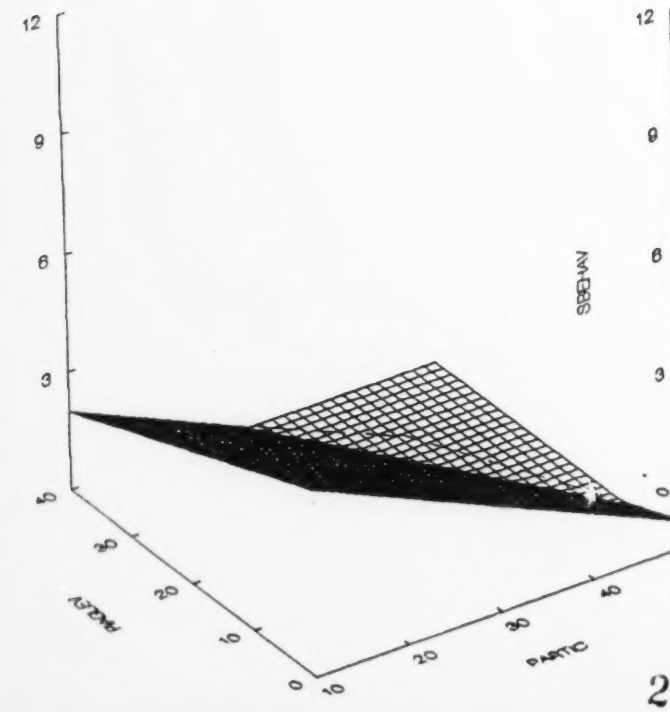
Solutions: Raw Data



Solutions DWLS Surface



Solutions: LS Plane



Solutions: Quadratic LS Surface